



HYBRID AI FRAMEWORK FOR FAIR AND SCALABLE INTERSHIP RECOMMENDATION

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Abstract: Internships are a bridge between academic learning and real corporate experience. Yet, most existing internship allocation systems are manual, biased, and inefficient, often leading to mismatches between student skills and organizational requirements. This paper proposes an AI-powered internship recommendation engine that combines Decision Trees for explainability, Hybrid Collaborative Filtering for accuracy, and Natural Language Processing (NLP) for skill extraction. To make the process fair, the system also includes fairness-aware filtering and a feedback loop for continuous improvement. Together, these components create a transparent, scalable, and equitable framework that helps students find the right internships while assisting companies in selecting suitable candidates.

Index Terms — Internship recommendation, Artificial Intelligence, Decision Tree, Hybrid Collaborative Filtering, NLP, Fairness, Corporate Sector

Introduction

Internships are crucial for shaping careers, as they provide students with industry-relevant exposure and practical learning opportunities. Unfortunately, most allocation methods used today are based on manual resume screening or academic grades, which often leads to biased, slow, and sub-optimal results. For instance, students may end up in roles unrelated to their abilities, while companies fail to connect with candidates who actually fit their needs.

Artificial Intelligence (AI) offers new possibilities in this area. In recent years, recommender systems have been widely applied in domains like e-commerce, healthcare, and education to deliver personalized and fair results. For example, Çakır et al. [1] demonstrated that deep hybrid models combining collaborative filtering with neural networks can improve recommendation accuracy. Similarly, Permana and Pradnyana [2] showed that competence-based systems align student skills better with internship opportunities.

Building on these foundations, this paper introduces a hybrid AI-powered recommendation system designed specifically for internship allocation in the corporate sector. Our approach blends Decision Trees (for explainability), Hybrid Filtering (for accuracy), and NLP-driven skill extraction (for semantic understanding). To ensure fairness, the model incorporates bias-aware ranking and a feedback mechanism so the system continuously learns and improves.

Literature Review

1. Deep Hybrid Models

Çakır et al. (2020) created a deep hybrid recommendation framework combining neural networks and collaborative filtering, which improved recommendation accuracy in large-scale systems [1].

2. Competence-Based Systems

Permana and Pradnyana (2019) proposed a competence-based AI system for student-internship alignment, ensuring that both academic knowledge and practical skills were considered [2].

3. Hybrid ANN Approaches

Afoudi et al. (2021) integrated Artificial Neural Networks with collaborative filtering, showing that hybrid models significantly enhance recommendation accuracy [3].

4. Systematic Reviews of Job Recommenders

Al-Walidi et al. (2024) reviewed existing job recommender systems, identifying challenges such as fairness, scalability, and cold-start problems [4].

5. Personalized Job Matching

Wang (2025) designed a personalized job matching algorithm that improved the efficiency of student–job allocations by considering student preferences [5].

6. Ontology-Based Internship Systems

Baya et al. (2017) applied ontology-driven frameworks for semantic mapping of student skills to job descriptions, enhancing the quality of internship placements [6].

7. Fuzzy Search Algorithms

Innovatus (2019) developed a fuzzy search-based internship recommender system, which effectively handled uncertain or incomplete student data [7].

8. Simple Additive Weighting (SAW) Approaches

Santoso et al. (2018) applied a SAW-based scoring system for internship recommendations, enabling fair and transparent ranking of opportunities [8].

9. Hybrid Collaborative Filtering Models

Rajganesh et al. (2018) implemented a hybrid collaborative filtering algorithm that balanced accuracy and personalization in job recommendations [9].

10. Resume Matching Systems

IJRASET (2025) introduced an AI-powered resume matching system that automated candidate–job alignment using intelligent filtering and scoring [10].

11. Hybrid Job Recommendation Systems

ICACC (2022) demonstrated the effectiveness of hybrid filtering methods in improving the performance of job recommendation systems [11].

12. Decision Tree Approaches

Jeevalatha et al. (2014) applied Decision Trees to student placement prediction, showing their interpretability and effectiveness in academic-to-industry mapping [12].

Problem Statement

1. **Mismatch** – Students are often placed in internships that do not align with their skills.
2. **Bias** – Preference is given to certain institutions, high GPA students, or well-known companies [4][8].
3. **Scalability** – Manual processes cannot handle large volumes of students and employers efficiently [5].
4. **Lack of Transparency** – Students are rarely informed why they were selected or rejected [12].

Methodology

1. Data Collection

- Collect student data: resumes, grades, and preferences.
- Collect employer data: job postings and skill requirements.
- Data sources include academic databases and company portals, forming the raw dataset required for model training and testing [5].

2. Preprocessing

- Clean and normalize the collected data.
- Remove duplicate or irrelevant information.
- Map extracted skills into a standardized taxonomy for consistency across resumes and job postings [10].

3. Skill Extraction (NLP Layer)

- Apply Natural Language Processing (NLP) models such as BERT and SBERT.
- Extract both technical skills (e.g., Python, SQL) and soft skills (e.g., teamwork, communication).
- Enable semantic similarity comparison between student resumes and job descriptions [6].

4. Recommendation Engine:

- **Decision Tree Layer**
- Generates transparent predictions.
- Explains to students and employers why a recommendation was made [12].
- **Hybrid Filtering Layer**
- Content-based filtering → matches skills and preferences.
- Collaborative filtering → uses similar student profiles and employer hiring history.
- Improves both accuracy and personalization [1][3][9][11].

5. Reciprocal Matching

- Matches students with internships by considering both student preferences and employer requirements.
- Ensures two-way fairness instead of one-sided allocation [5].

6. Fairness-Aware Filtering

- Adjusts rankings to reduce bias towards elite institutions, high-GPA students, or well-known companies.
- Ensures equal opportunity for all students [8].

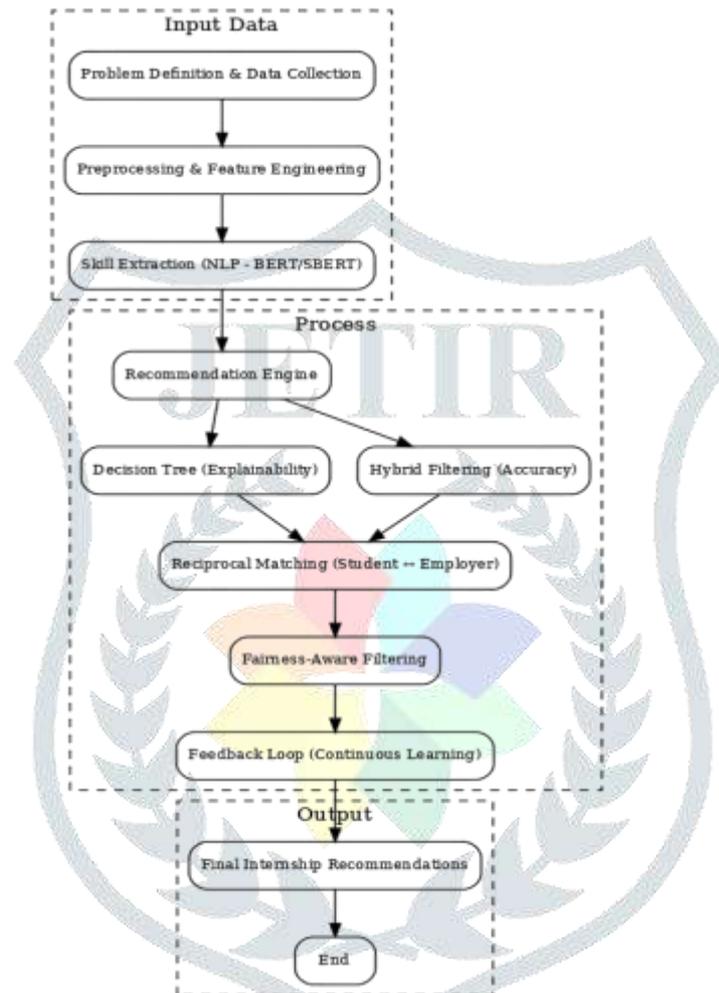
7. Feedback Loop

- Use feedback to retrain the model.
- Improve recommendation quality and fairness over time [7].

8. Deployment

- Provide dashboards for universities, students, and companies.
- Cloud deployment ensures:
 - Scalability → handles large volumes of data.
 - Accessibility → available across multiple institutions [9].

Flowchart (Execution Plan)



The proposed framework begins with data collection and preprocessing, where student and employer data are cleaned and structured. NLP models such as BERT or SBERT extract relevant skills from resumes and job descriptions. The recommendation engine then combines decision trees for explainability and hybrid filtering for accuracy to generate internship matches. A reciprocal matching stage ensures alignment between student preferences and employer needs, followed by fairness-aware filtering to remove bias. Finally, a feedback loop continuously improves the system, producing fair and scalable internship recommendations.

Ethical Implications

2.1 Fairness and Equal Opportunity

The system must prevent bias based on gender, background, or institution, ensuring fair access for all students [8].

2.2 Transparency and Trust

Decision Trees make recommendations explainable, which builds accountability and confidence among students and universities [12].

2.3 Privacy and Responsibility

Student and employer data must be securely stored, and algorithms must avoid reinforcing existing inequalities [4][10].

Legal Implications

3.1 Data Protection and Consent

Compliance with GDPR, Indian IT Act, and CCPA is required, with explicit student consent for resume analysis [4][10].

3.2 Corporate Compliance

Recommendations must align with university placement policies and HR regulations in the corporate sector [5].

3.3 Intellectual Property

Ownership of datasets, models, and recommendation algorithms must be clearly defined to avoid legal disputes [11].

Technical Implication

4.1 Cold Start and Scalability

New students/employers must still be matched fairly, and cloud deployment is needed to handle large-scale data [5][7].

4.2 Accuracy vs Explainability

Decision Trees provide interpretability, while hybrid deep models offer higher accuracy, requiring a balance [1][3][12].

4.3 System Integration

The framework must integrate with existing ERP systems and corporate job portals for smooth adoption [9].

Conclusion

This research proposes an AI-powered internship recommendation system that integrates Decision Trees, Hybrid Filtering, and NLP-based skill extraction. By embedding fairness-aware filtering and feedback loops, the system ensures equal opportunities for students while helping companies select the right candidates. Future work includes scaling to larger datasets, using multilingual NLP models, and real-world deployment in academic and corporate environments.

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